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ABSTRACT

As useful as LISREL may be in model estimation and testing, its most significant contribution to date is the encouragement and example it gives for right thinking about research and right planning of research. The encouragement to hypothesize the best possible model for the process that is the object of study, and to plan measurements that adequately specify the model, is the aspect of LISREL which is transforming educational research. The estimated model encourages researchers to believe that criterion achievement was heavily influenced by input achievement and modestly influenced by input attitude, but not by instructional process. If the major question of instructional process research is whether the measurement of instructional process variables yields information which contributes to the explanation of learning variance, the answer given for this example by the FaM model squares with the answer given by the LISREL model. The newest version of LISREL redresses previous grievances indicating that it is going to be easier to compute and interpret LISREL models. (Author/PN)

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EMPIRICAL ESTIMATION OF THE MODEL PARAMETERS BY USING LISREL

by

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SUNY at Buffalo

Paper presented at AERA Symposium on the Causal Modeling Process, NYC, 3/21/82

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Empirical Estimation of the Model Parameters by Using LISREL

Paul R. Lohnes and Lu Pai, SUNY at Buffalo

Dr. Gagne has described a theory that is capable of guiding research on instruction. Drs. Gallini and Bell have shown how a causal model for research data on instruction can be formulated under the guidance of Dr. Gagne's theory. The really big problem is to design measurements of instructional tasks and instructional outcomes such that the correlations (or covariances) among them will have the causation ascribed to them by the apriori model. The model estimation and evaluation problems discussed in our paper and Dr. Bentler's paper do not loom large by comparison. For example, the theory we are talking about may lead to a simplex model being hypothesized. "The simplex model is equivalent to the covariance structure generated by a first-order non-stationary autoregressive process" (Jöreskog & Sörbom, 1981, p. III.71). See Kenny (1979, pp. 173-180) for a good discussion and standard references on this very strong theory for data. The LISREL V manual (Jöreskog & Sörbom, 1981, pp. III.70-III. 81) provides as Example III.7 a very helpful guide to analysis of a simplex. We emphasize that in our judgment the biggest problem is to design research measurements and situations that will generate data by an autoregressive process.

Our posture today is that of the shepherd who has just seen a magnificent star rise in the East (in this case, over Uppsala). We had intended to complain vigorously about the difficulties we find in using LISREL and the information we want that it doesn't give us, even as we would grudgingly admit that it has special advantages as a model estimation procedure. We have been using LISREL IV. While we were finishing our paper, a handsome red book titled LISREL V showed up in our mail. Immediately we opened it, a great light shone. The very brief PREFACE promised redress of all our grievances. Automatic starting values would be provided. Cheap initial estimates by least squares with instrumental variables would be made, and they would usually be "very close to the final solution" from the maximum likelihood method. Variance explained by each equation in the model would be reported. Also, "The decomposition of total causal effects into direct and indirect causal effects" would emerge. The all-important B estimates would come out with the right signs. Then on page I.6 a new and satisfying

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formulation of the basic structural equation was revealed:

$$\eta = B\eta + \Gamma\xi + \zeta$$

Now that B is on the right side of the equal sign, it becomes a matrix "which has zeros in the diagonal and contains the direct effects of each η on other η's." So it is a subdued critic who appears before you today to say that LISREL looks better than ever.

LISREL estimation of models of instruction facilitates the fitting of models in which cause and effect flow forward over time, so that ends-in-view at one point in time become means to further ends-in-view at a later point in time, and this rhythmic conversion of ends into means into ends into means into ends provides the pulses which are recorded as measurement events in the study of an instructional process. LISREL encourages hypotheses about correlatedness of measurement errors when the same technique is used to collect observations at different time points. LISREL permits the simultaneous estimation of a structural model for the causal paths among the latent variables and a measurement model for the observational variables. Most basically, LISREL encourages us to employ latent variables as the causal factors underlying what we see and measure, which is an improvement in our way of thinking over the habits encouraged by OLS and path analysis, an improvement of tremendous importance. Dr. Bentler makes this very clear in his marvelous chapter in the 1980 Annual Review of Psychology. That is to say that useful as LISREL may be in model estimation and testing, its most significant contribution to date is the encouragement and example it gives us for right thinking about research and right planning of research. The encouragement to hypothesize the best possible model for the process we intend to study, and to plan measurements that adequately specify the model, is the aspect of LISREL which is transforming educational research for the better. Of course this movement is under the influence of other significant writers, including Bentler (1980), Kenny (1979), and Heise (1975).

When Cooley and I surveyed the instructional research scene in our 1976 evaluation text, we concluded about many of the existing researches that "these previous efforts have not been guided by any particular theory of instruction, and thus may have included some rather irrelevant variables or, more importantly, may have omitted critical aspects of the instructional process" (Cooley & Lohnes, 1976, p. 184). We then attempted to combine theoretical contributions of Gagne, of Glaser, and of Carroll into a model of classroom processes that hypothesized a set of latent variables and a structure of causal relationships among them (Figure 5.4, p. 191). We hoped that paradigms

similar to ours would come to guide instructional research. That's what has been happening, and LISREL has had a profound influence in that direction.

One of the problems with data analysis guided by strong apriori theory is that the theory may be bad and may poison the analysis. Our old-fashioned methods of heuristic multivariate analysis often allowed the message in the data to shine through our preconceptions. We wanted to say today that a LISREL-estimated model should be embroidered at its edges with certain supplementary descriptions of how well it fits the data. One wants to know how much of the variance of each of the observed variables is explained by all the paths to it from the latent variables (hereafter "factors"), how the explanation of variance is partitioned among the factors, and all the correlations between variables and factors. Apparently it is going to be easier to get these embroideries from LISREL V that it has been from LISREL IV.

We have had to compute our example by means of LISREL IV (handout). The data we borrowed from John Keeves (1974) excellent Australian research. For these data it was possible to hypothesize

(1) two essentially independent factors of aptitude;

(2) an instructional process factor which was partially caused by APT:ACH (because students and teachers interact in ways which are conditioned by their views of the student's ability in the subject);

(3) direct influence of all three causal factors on the criterion achievement factor and indirect influence of APT:ACH on the criterion mediated by INSTR PROC;

(4) correlation between disturbances for the two maths tests, and for the two science tests.

The estimated model encourages us to believe that criterion achievement was heavily influenced by input achievment and modestly influenced by input attitude, but not by instructional process. Also, we are told that the variance in instructional process was moderately conditional upon the variance in input achievement. (APT:ACH, INSTR PROC, and CRITERION are the η factors, and the coefficients along paths connecting them are the B estimates, where the η are the dependent factors; APT:ATT is the ξ factor, and the coefficient along the path connecting it to the CRITERION factor is the Γ estimate, where ξ is the independent factor. To get the correlated errors into the model where we wanted them we had to make this weird designation of the factors. The paths from the factors to the variables z are estimated by the coefficients Λ of the measure-

ment model for the observations, which is $z = \mathcal{A}(\eta:\S) + (\varepsilon:\delta)$, and these coefficients are scaled relative to those among them which were forced to 1.0 to make the estimation possible.)

The correlated disturbances helped to provide a better fit of model to data. Without them $\chi^2_{19} = 84$, $p(H_o) = .0000$. Well and good, but alas, there are signs besides the awfully large chi-square that the model as reported is inadequate (including computed negative variances and correlations larger than 1.0). Of the 28 correlations among the variables, 8 are equalled by their residuals because the model asserts that they should be zeros, and 5 others are matched to residuals that are unacceptably large. Thus only 15 of 28 observed correlations achieve satisfactory explanation. It's probably our ignorance showing, but we have not been able to determine how much of each of the observed variances is explained by the factors of the model, nor how each is partitioned by attributions to specific factors.

The reverse side of the handout reports an alternative analysis of the same data, inspired by the same theory, but estimated (if that's not too strong a word) by FaM (Lohnes, 1979). As Lee Wolfle, who was one of the first and most generous correspondents about FaM, pointed out, FaM provides only a measurement model for the variables, since it constrains the factors to mutual orthogonality, thus precluding a structure amongst them (although a hierarchical ordering of the factors is part of the hypothesis). Too bad, but if one wants to understand the correlations among the variables, not the etiology of the factors, what one gets from FaM may be helpful. FaM provides the multiple regressions of the variables on the factors as structural equations for the variables in terms of the factors. The partition of explained variance is totally unambiguous, if not totally convincing. The factors can be scored, which may be useful in some research programs, and does tend to demystify them. Granted that the analysis is quick and dirty, it may be that when its product is judged for its own merits rather than for its mathematical genesis, it seems often to be a worthy product. Isn't the pattern of residual covariances for this example a nice one? If the major question of instructional process research is whether the measurement of instructional process variables yielded information which contributed to the explanation of learning variance, the answer given for this example by the FaM model squares with the answer given by the LISREL model.

The newest version of LISREL shows that it is going to be easier to compute and interpret LISREL models. There may be other useful ways to estimate the models of interest to us. The act of modeling has a future with us.

References

Bentler, P. M. Multivariate analysis with latent variables: causal modeling. Annual Review of Psychology, 1980, 31, 419-456.

Cooley, W. W., & Lohnes, P. R. Evaluation research in education. NY: Irvington/Wiley, 1976.

Heise, D. R. Causal analysis. NY: Wiley-Interscience, 1975.

Jöreskog, K. G., & Sörbom, D. LISREL V: analysis of linear structural relationships by maximum likelihood and least squares methods. Uppsala, Sweden: University of Uppsala, Department of Statistics, 1981.

Keeves, J. P. The performance cycle: motivation and attention as mediating variables in school performance. Home Environment and School Study Report 5. Melbourne: Australian Council for Educational Research, 1974.

Kenny, D. A. Correlation and causality. NY: Wiley-Interscience, 1979.

Lohnes, P. R. Factorial modeling in support of causal inference. American Educational Research Journal, 1979, 16, 323-340.

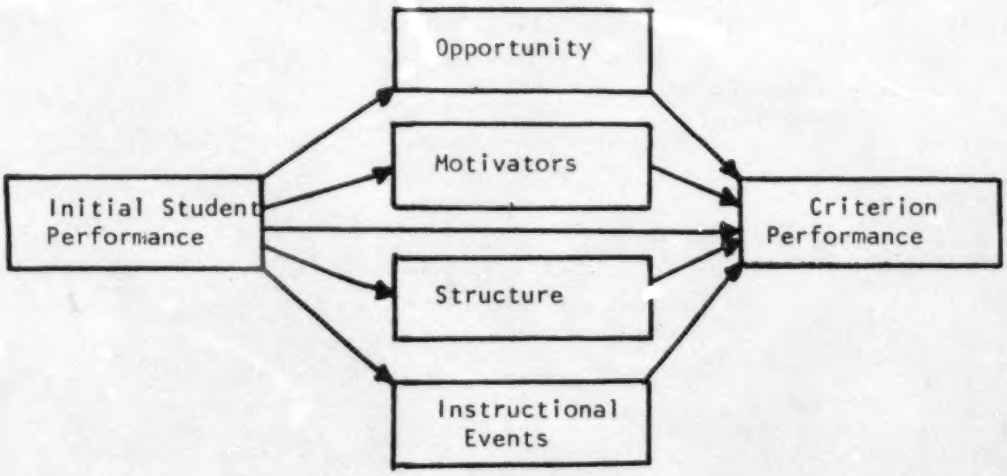


Figure 5.4: Model of Classroom Processes (Cooley & Lohnes, 1976, p. 191)

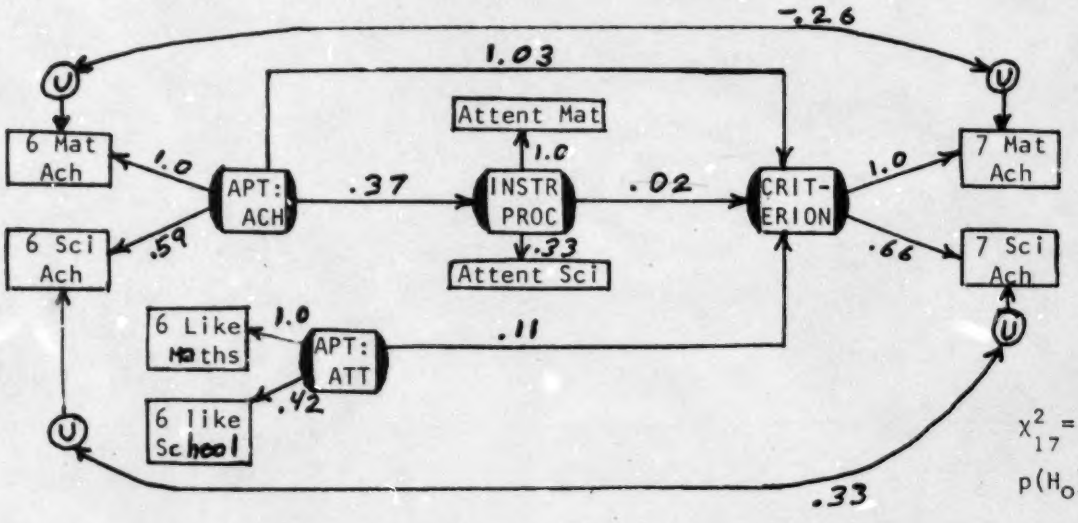
AERA Handout, NYC March 21,1982. Paul R. Lohnes, 379 Baldy Hall, SUNYAB, Amherst and Lu Pai NY 14260

Data Matrix

Keeves, J. P. The performance cycle. Home Environment and School Study Report 5. Melbourne: Australian Council for Educational Research, 1974.

Factor	Variable								
APT: ACH	6 Maths Ach	(1) 1.00							
	6 Science Ach	(2) .62	1.00						
APT: ATT	6 Like Maths	(3) .20	.06	1.00					
	6 Like School	(4) .17	.13	.41	1.00				
INSTR PROC	Attentive Mat	(5) .39	.21	.02	.05	1.00			
	Attentive Sci	(6) .24	.14	.09	.09	.37	1.00		
CRITERION	7 Maths Ach	(7) .83	.64	.26	.22	.41	.24	1.00	
	7 Science Ach	(8) .73	.76	.12	.20	.29	.25	.78	1.00

Model Estimated by LISREL IV



$\chi^2_{17} = 31$

$p(H_o) = .02$

LISREL Residual Matrix

Var	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	.037							
(2)	.027	.020						
(3)	.200	.060	-.017					
(4)	.170	.130	-.007	-.003				
(5)	.025	-.006	.020	.050	-.018			
(6)	.120	.069	.090	.090	-.003	-.003		
(7)	.051	.026	.154	.176	.011	.109	.055	
(8)	.047	.028	.050	.171	.027	.163	.044	.037

Correlations with Factors

	I	II	III	IV
(1)	.98	.00	.34	.98
(2)	.57	.00	.20	.58
(3)	.00	.99	.00	.10
(4)	.00	.42	.00	.04
(5)	.35	.00	.99	.38
(6)	.12	.00	.35	.12
(7)	.99	.11	.37	.99
(8)	.66	.07	.25	.70

Correlations Among Factors

		I	II	III	IV
I	APT:ACH	1.00			
II	APT:ATT	.00	1.00		
III	INSTR PROC	.34	.00	1.00	
IV	CRITERION	.98	.10	.36	1.00

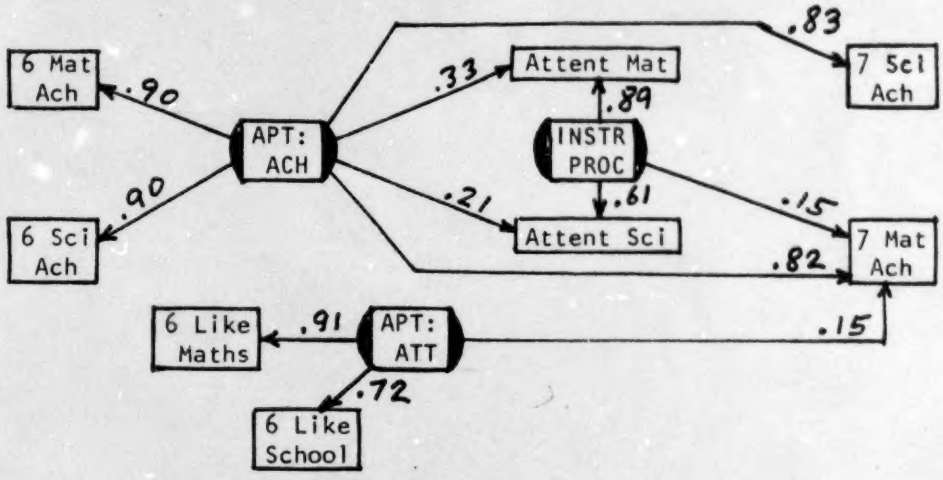
Distributor of LISREL V Manual and Computer Program:

International Educational Services
1525 East 53rd St., Suite 829
Chicago IL 60615
(312) 684-4920

Model Estimated by FaM (Uncorrelated Factors)

Variable	Factors I	II	III	d	$h^2=R^2$
6th Year Mathematics Achievement	.90	.06	.10	.43	.816
6th Year Science Achievement	.90	-.06	-.10	.41	.831
6th Year Liking for Mathematics	.14	.91	-.01	.40	.843
6th Year Liking for School	.17	.72	.01	.67	.547
Attentiveness in 7th Maths	.33	-.02	.89	.31	.902
Attentiveness in 7th Science	.21	.07	.61	.76	.418
7th Year Mathematics Achievement	.82	.15	.15	.54	.706
7th Year Science Achievement	.83	.03	.04	.56	.688

Interpretable Paths Estimated by FaM



FaM Residual Matrix

Var	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	.184							
(2)	-.176	.169						
(3)	.015	-.015	.157					
(4)	-.026	.025	-.267	.453				
(5)	.006	-.005	-.001	.001	.098			
(6)	-.013	.013	.001	-.002	-.239	.582		
(7)	.076	-.073	.013	-.022	.013	-.031	.294	
(8)	-.018	.017	-.024	.041	-.020	.049	.095	.312

Factor Score Coefficients

	FI	FII	FIII
(1)	.544	-.098	-.199
(2)	.567	-.103	-.207
(3)	0	.751	-.004
(4)	0	.443	-.002
(5)	0	0	.878
(6)	0	0	.360
(7)	0	0	0
(8)	0	0	0